



## Original Articles

# Count population viability analysis finds that interacting local and regional threats affect the viability of a rare plant



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## ABSTRACT

Ensuring the best use of limited conservation resources requires comprehensively assessing the relative importance of multiple threats, some of which occur at local and some at regional spatial scales. Multiple threats are rarely modeled in traditional population viability analyses (PVA) due to the high data requirements necessary to parameterize age or stage based population models. Count based PVAs have been shown to provide robust results, and count data are readily available from many monitoring programs. Despite this, we are not aware of any studies that have used count based PVAs to assess multiple threats for plant populations. To demonstrate the utility of count based PVAs of assessing multiple threats at multiple spatial scales, we use long-term monitoring data by the Chicago Botanic Garden's Plants of Concern program to assess the main and interactive effects of two local threats (woody invasive species, browsing by deer) and one regional threat (climate change) on the viability of the rare forb, *Eurybia furcata*. We found an interaction between local and regional threats, which suggests that management actions targeting local threats can improve the viability of *E. furcata* populations both by directly reducing the risk of extinction and indirectly by decreasing this species vulnerability to climate change. Therefore, we recommended that land managers prioritize local scale management, specifically woody invasive species encroachment, to reduce this species' overall risk of extinction. The threat of climate change will act in concert with other anthropogenic factors, but conservation planning has historically focused on local scale threats. Adapting management to consider the regional threat of climate change requires threat analysis from multiple populations and at regional spatial scales. This task may seem daunting, but our results provide an optimistic outlook that count data can be effectively utilized for this purpose. Applying this approach widely to count based monitoring data already in existence would result in robust recommendations to land managers for many species of concern.

## 1. Introduction

The best spatial scale for management of a species depends on which factors most threaten populations within a region and how those factors interact (Oostermeijer, 2003; Brook et al., 2008). If a local scale threat, such as an herbivore or invasive competitor, has large effects on population viability, then local scale management aimed at removing the threat and monitoring to ensure that the population size increases should be the conservation priorities (e.g. Vitt et al., 2009). If a regional scale threat, such as climate change, has large effects on population viability, then regional scale management such as prioritizing populations best positioned for persistence for increased conservation effort

should be implemented in response (e.g. Lendvay and Kalapos, 2014). Lastly, if both local and regional scale threats affect population viability, management effort should be balanced to create the best chance for long term persistence (e.g. Marrero-Gómez et al., 2007; Phillips-Mao et al., 2016). For example, in a review of conservation options for four species endemic to Southern Florida, Maschinski et al. (2011) found that local scale management, such as removal of invasive species, could only decrease these species' extinction risks in the short term. In the long term, no local management option was predicted to be effective against climate change induced sea level rise. Only managed relocation to higher elevations had the potential to prevent the extinction of these species. Thus, the authors recommended balancing management

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efforts, enacting local scale management only to increase these species' chances of persistence while the necessary research and legislative actions are taken to enact managed relocation.

Management at both local and regional scales can be costly (Walpole and Al., 2009; Maschinski et al., 2011), so to ensure the best use of limited conservation resources it is important to comprehensively assess the relative importance of multiple threats to inform management plans. For terrestrial plant species, quantifying the effects of threats (e.g. Maschinski et al., 2006; Pardini et al., 2015) and determining management strategies (e.g. Bernardo et al., 2016; Menges, 2007) are typically done with stage or age based population viability analyses (PVA) or integral projection models (Crone et al., 2011). These methods require quantitative data on the demography of multiple populations over long time periods (> 10 years; Morris and Doak, 2002). These long-term demographic data rarely exist (Eldred et al., 2003), and even when they do, many studies cannot consider multiple threats because doing so further increases the data required (but see e.g. Bowles et al., 2015; Phillips-Mao et al., 2016; Souther and McGraw, 2014).

However, long-term population count data are much more readily available through, for example, large scale plant monitoring programs (Parks, 1993; Bittman, 2001; Havens et al., 2012). Count data are much less laborious to collect than stage or age based demographic data and can often be collected over longer periods of time and for more populations within a region. There have been calls for better use of count data in rare plant species management for almost two decades (Morris et al., 1999; Eldred et al., 2003; Bakker and Doak, 2008), and there is now good evidence that count based PVAs can be used similarly to age or stage based PVAs when comparing relative extinction risk and developing management plans (McCarthy et al., 2002; Morris and Doak, 2002; Lotts et al., 2004; Sabo et al., 2004; García et al., 2010). Despite this, only a few peer-reviewed studies have used count based PVAs to assess the effects of threats on plant species (DePrenger-Levin et al., 2010; Molano-Flores and Bell, 2012; Morris et al., 1999; Ramula et al., 2008; Thomson and Schwartz, 2006), but none of these studies have used the method to compare among many threats acting at different spatial scales. Here, we extended the traditional count based PVA approach to assess the relative effects of multiple, interacting threats acting on different spatial scales for *Eurybia furcata*, a rare, woodland forb endemic to the Midwestern USA. Our approach provides solid recommendations to land managers about whether they should prioritize local scale management of their individual populations, network with other managers to conduct regional scale management, or some combination of both.

We used a modified count based PVA projection technique to determine the scale dependent management needs of *E. furcata* in response to multiple threats. First, we assessed the relative main and interactive effects of two local threats, encroachment by woody invasive species and browsing by deer, by associating *E. furcata*'s growth rate values with varying threat levels. Second, we assessed a regional threat, climate change, by associating *E. furcata*'s growth rate values with historic and future climatic conditions. Last, we assessed the interactive effects between threats at a local versus regional scale.

## 2. Materials and methods

### 2.1. Study system

*Eurybia furcata* (Burgess) G.L. Nesom, formerly *Aster furcatus*, is a perennial, woodland herb endemic to the Midwest USA (Les et al., 1992). It is known to occur in six states (Fig. 1) but has only two large concentrations of populations, one in Southern Missouri and one in upper Illinois/lower Wisconsin (Les et al., 1992; NatureServe, 2016). It is listed as vulnerable, endangered or critically endangered by NatureServe in all six states (NatureServe, 2016) and has state level Threatened status in five states (IA, IL, MI, MO & WI; USDA and NRCS, 2016).

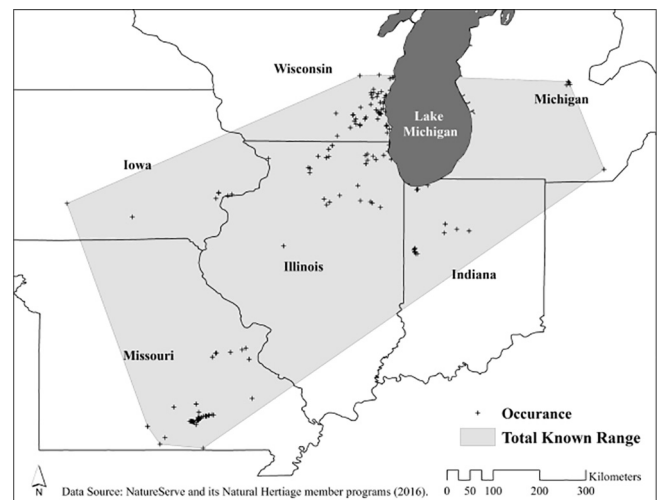


Fig. 1. Map of the Midwestern United States showing all known current and historic occurrences of *Eurybia furcata*. This information is provided by NatureServe (NatureServe, 2016; [www.natureserve.org](http://www.natureserve.org)) and its Natural Heritage member programs, a leading source of information about rare and endangered species, and threatened ecosystems.

*Eurybia furcata* is found in isolated patches on north-facing woodland slopes (Les et al., 1992). It reproduces both sexually and asexually via rhizomes, sometimes forming dense patches of genetically identical individuals (Les et al., 1991, 1992). The major threats to *E. furcata* are thought to be habitat loss (NatureServe, 2016), loss of genetic variation (Les et al., 1991; Reinartz and Les, 1994), encroachment by woody invasive species and browsing by White-tailed deer (R. Goad pers. obs.).

This species is ideal for a count based assessment. First, sexual reproduction is rare because it is limited by a self-incompatibility system and generally low levels of genetic variation within populations (Les et al., 1991; Reinartz and Les, 1994). This means that *E. furcata* likely does not form large dormant seed banks, which could bias above ground population size counts. Infrequent sexual reproduction also means seedlings are rare, and since even small individuals are easily identifiable, thus the likelihood of observer bias in population size counts is low. Lastly, our monitoring data do not suggest a tendency for extreme fluctuations in population size, which can bias population projection results (Morris and Doak, 2002). Therefore, using population size counts based on the number ramets is likely to provide a representation of this species short-term population dynamics that is sufficient for comparatively assessing the effects of various threats to this species' persistence (Eriksson, 1994; Colling and Matthies, 2006).

### 2.2. Data collection

The Chicago Botanic Garden's Plants of Concern (POC) program (Havens et al., 2012) is a citizen science initiative that tracks the population size of, and local threats to, rare plants in Northern Illinois, Northwest Indiana and formerly in Southeast Wisconsin (hereafter referred to as the Western Great Lakes region). The data used in this study are from seven populations of *E. furcata* in Illinois and Wisconsin monitored from 2001 to 2015 (Appendix S1: Table S1). For logistic purposes, when populations have two or more patches separated by 50 m or more, those populations are broken into subpopulations treated as independent units for data collection. There are 21 subpopulations being monitored across the seven populations. Monitoring occurs once per subpopulation per year during peak flowering. Data for a variety of attributes are collected. The relevant data for these analyses are: 1) the total number of individuals (N), 2) stem density (N/area), and 3) the categorical impact of two local threats (woody invasive species encroachment and browsing by deer) as no impact (0%; no woody

invasive species present or no deer browsing observed), low impact (1–50% of the *E. furcata* subpopulation affected by the threat) or high impact (51–100% of the *E. furcata* subpopulation affected by the threat). For full program details and methods see [www.plantsofconcern.org](http://www.plantsofconcern.org).

An internal review of data quality showed that POC volunteer monitors reported identical estimates as highly trained Chicago Botanic Garden staff for population size (measured by categories), woody invasive encroachment categories and deer browsing categories 80%, 73% and 85% of the time, respectively (Havens et al., 2012). Despite the high measured congruence between volunteer and expertly collected data, monitoring events were removed if the associated field notes indicated that the subpopulation size count was likely inaccurate (e.g. a known section of a population was not visited; 7 total; not included in Table S1), or marked as suspect if the notes indicated a subpopulation size count might be inaccurate (e.g. poor weather or site conditions made monitoring difficult; 3 total; included in Table S1). One of these three points tested as a significant outlier using Studentized residuals (stats::rstudent) in all tests and so was removed from projection analyses. All statistics were done in R version 3.3.2 (R Core Team, 2016).

### 2.3. Count based population viability analysis (PVA)

All of our analyses use a basic count based, stochastic population projection modeling procedure (Dennis et al., 1991; Morris and Doak, 2002). First, the change in subpopulation size from one monitoring event ( $N_t$ ) to the next ( $N_{t+1}$ ) was calculated as a log response ratio (LRR):

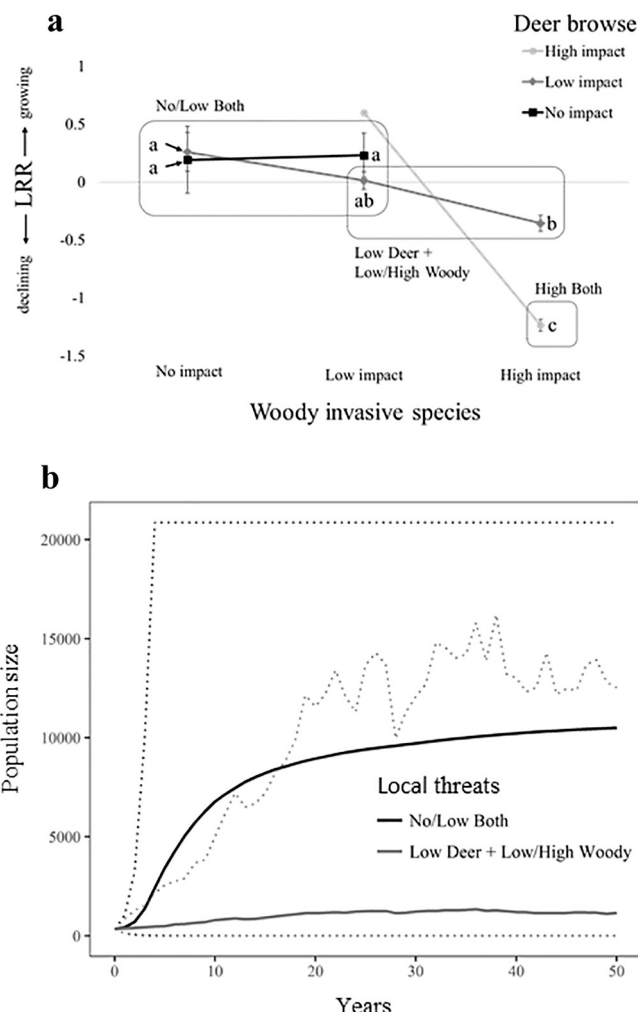
$$\text{LRR}_{t \rightarrow t+1} = \ln(N_{t+1}) - \ln(N_t) \quad (1)$$

The LRR is a population growth metric with a critical value of zero; above zero is growth and below zero is decline. Then, we stochastically projected population size 50 years into the future by performing 50 iterations of eq(2), randomly choosing a different LRR value from the observed data for each iteration:

$$N_{t+1} = N_t * \exp(\text{LRR}) \quad (2)$$

We ran 1000 replicate projections of this 50-year simulation to calculate the probability of extinction. Using a quasi-extinction threshold of ten individuals, the probability of extinction was the number of replicate projections that fell below ten individuals divided by 1000. We included a carrying capacity (K) as a ceiling in the projection model by reducing a projected population's size down to K ( $N_t = K$ ) only when  $N_{t+1} > K$ . This was done despite no detectable density dependence (assessed by regressing stem density against LRR;  $F_{1,73} = 1.52$ ;  $r = 0.007$ ;  $P = 0.22$ ) to prevent population sizes from becoming unrealistically large. The starting population size and K of each replicate projection were 343 and 20,868, respectively. These starting parameters were the median population size and carrying capacity (calculated as the number of stems \* the maximum observed stem density) for all subpopulations monitored by the POC program.

Not all LRR values recorded from a site could be used in these analyses. First, extremely small populations (defined here as ten individuals or less) can be problematic for this method because small populations sizes typically fluctuate due to demographic stochasticity, whereas the count based approach assumes population sizes fluctuate due to environmental stochasticity. For this reason, all LRRs in which either  $N_t$  or  $N_{t+1}$  from Eq. (1) was less than or equal to ten individuals were removed (10 total; not included in Table S1). Also, to incorporate the effect of threats into our count based PVA projections (explained in detail next), we assumed that the level of a threat or the climatic conditions during the year that  $N_t$  from Eq. (1) was recorded is at least partly responsible for the change in size from  $N_t$  to  $N_{t+1}$ . Thus, only LRRs calculated from single year transitions were used in these analyses.



**Fig. 2.** (A) Results of independent contrast ANOVAs to test the main and interactive effects of woody invasive species encroachment and deer browsing on the average annual change in population size (LRR) of *Eurybia furcata*. Differences at a  $p > 0.1$  threshold bolded. Pairwise Tukey's test results marked with †. Test Results: No versus low impact of deer with no impact of woody species ( $F_{1,9} = 0.04$ ;  $p = 0.85$ ); No versus low impact of deer with low impact of woody species ( $F_{1,52} = 1.03$ ;  $p = 0.32$ ); Low versus high impact of deer with high impact of woody species ( $F_{1,8} = 62.33$ ;  $p < 0.001$ ); No versus low impact of woody species with no impact of deer ( $F_{1,13} = 0.02$ ;  $p = 0.90$ ); No versus low versus high impact of woody species with low impact of deer ( $F_{2,53} = 2.70$ ;  $p = 0.08$ ) — No versus low impact of woody species with low impact of deer† ( $p = 0.51$ ); No versus high impact of woody species with low impact of deer† ( $p = 0.08$ ); Low versus high impact of woody species with low impact of deer† ( $p = 0.14$ ). (B) Model results examining the effects of local threats. Solid lines show the change in population size through time averaged across the 1000 replicate simulations for each scenario. Dotted lines are 95% CIs around the mean.

### 2.4. Modeling local threats

The data and R code for the remainder of our methods are available through GitHub (<https://github.com/hollybernardo/Count-based-Threat-Assessment>). We assessed the effects of woody invasive species encroachment, browsing by deer and their interaction on LRR at the subpopulation level (GitHub Data S1). We considered subpopulation to be the appropriate level of replication because both threats vary across small spatial scales. Sample sizes were low or data were missing in some combinations of the threat categories. We tested whether treatment combinations were different from each other using independent contrast ANOVAs (Fig. 2a). There was only a single data point in the low

woody invasive and high deer browse combination and no data for the no woody invasive and high deer browse combination. Therefore, we could not assess mean LRR for these treatments. This lack of data could be due to the biology of these factors because deer are known to prefer woodland sites heavily invaded with exotic shrubs (Allan et al., 2010).

We modeled the effects of these local threats on future population size and extinction risk. We pooled categories that were not different at a  $P > 0.1$  threshold based on our independent contrast ANOVAs. This identified three scenarios for modeling (Fig. 2a): 1) no or low (0–50%) impact of deer browse with no or low impact of woody invasive encroachment (No/Low Both); 2) low (1–50%) impact of deer browse with either low or high (1–50%) impact of woody invasive encroachment (Low Deer + Low/High Woody); and 3) high (> 50%) impact of both deer browse and woody invasive encroachment (High Both). The sample size for each scenario was 64, 51 and 3, respectively, therefore we did not attempt projection modeling with the third scenario. We extracted the mean and standard deviation of the frequency distribution of LRR for the first and second scenarios (Appendix S2: Step 1 in Figure S1a). Then, we selected random LRR values from a normal distribution with those same parameters to perform 50-year stochastic projections under each scenario using eq(2) (Appendix S2: Step 2 in Figure S1a) replicated 1,000 times (Appendix S2: Step 3 in Figure S1a). We set population size to zero if it fell below one individual for the duration of the 50-year projection. These models assess the relative magnitude of effect of these local threats by the difference in the probability of extinction and the average final population size compared among modeling scenarios. Therefore, our results should not be interpreted as absolute estimates of *E. furcata*'s viability.

## 2.5. Modeling regional threat of climate change

We assessed the effects of climate change at the population level (GitHub Data S2). We considered this to be the appropriate level of replication because: 1) all subpopulations are close enough spatially that they should experience similar weather, and 2) the lowest resolution historic climate data available are at approximately 1 km<sup>2</sup>, which does not allow for differentiation among subpopulations. When multiple subpopulations were monitored in the same years, resulting in more than one LRR estimate per population per single year transition, we averaged the LRR values across subpopulations within each transition ( $n = 40$ ).

We chose to model the potential future climate of the Western Great Lakes region based on a downscaling of worldwide climate data by Hayhoe et al. (2010). Hayhoe et al. (2010) predicted the potential future climate of a small geographic region that included all our study populations and presented their results within explicit timeframes which allowed us to match the timing of the climate predictions to the length of our projection models. They predicted two major climatic changes in our region by 2050, a 10% increase in precipitation and a 2–3 °C increase in average temperature. The increase in precipitation is most likely to occur in the winter and spring months, therefore, we modeled a 10% increase in the combined total winter and spring precipitation (Table 1). The increase in temperature is predicted to occur

during the winter months up until about 2050 when winter temperatures are predicted to level off and summer temperatures are predicted to begin rising. Therefore, we modeled this warming as a 2 °C increase in average winter temperature throughout our 50-year projection, along with a 1 °C increase in average summer temperature beginning at year 36 of our 50-year projection (which is 2051 if we assume our model started in 2015). Because we choose variables that represent only the major climatic changes expected, the results of our models should be interpreted as *E. furcata*'s vulnerability to climate change given the major climatic changes that populations in the Western Great Lakes region are likely to experience.

We used local weather station data to determine the association between climatic variables and the population level LRR of *E. furcata* using multiple regression. Those data were obtained as a monthly average for the average daily temperature (°C) and a monthly total for precipitation (mm) from the National Center of Environmental Information (Lawrimore, 2016). We used data from the closest station to each population to represent that population's local conditions. *Eurybia furcata* is typically monitored in August so we defined its demographic year from fall-to-summer ( $N_t$  - > fall - > winter - > spring - > summer - >  $N_{t+1}$ ), and extracted weather variables from that time frame for each transition. We pooled climate data within each transition year (averaged for temperature; summed for precipitation) across meteorological seasons (fall = Sept–Nov; winter = Dec–Feb; spring = Mar–May; summer = June–Aug) to match Hayhoe et al. (2010). Thus, each LRR has an associated total winter plus spring precipitation (WSprec), average winter temperature (WINtemp) and average summer temperature (SUTemp).

We assessed the role of population, year, winter/spring precipitation (WSprec), winter temperature (WINtemp), and summer temperature (SUTemp) on LRR. We used AIC model selection (stats::step) to compare a baseline multiple regression model containing only the main effects of each climate variable ( $LRR \sim WSprec + WINtemp + SUTemp + 0$ ) to more complex models also considering main effects of population and year and interactions among climate variables (full model:  $LRR \sim WSprec + WINtemp + SUTemp + population + year + WSprec*WINtemp + WINtemp*SUTemp + WSprec*SUTemp + WSprec*WINtemp*SUTemp + 0$ ). The baseline model including only main effects had the lowest AIC score. Several significant ( $P < 0.05$ ) correlations were found among the climate variables but all were weak ( $r < 0.7$ ), so no variables were dropped from the final model. Lastly, we extracted the correlation coefficients ( $\beta$ 's) associated with each variable (WSprec = 0.0004; WINtemp = -0.0392; SUTemp = -0.0143) to allow us to calculate predicted LRRs for use in projection modeling (Appendix S2: Step 1 Figure S1b).

To calculate predicted LRRs given climate change, we first had to quantify the historic climate of our region. To do this, we used Current Climate data (~1960–1990) obtained from Worldclim 1.4 (Hijmans et al., 2005), then estimated future conditions by changing the historic conditions as predicted by Hayhoe et al. (2010). We obtained Worldclim data as monthly estimates of average daily temperature (°C) and total precipitation (mm). In ArcGIS 10.4.1, we placed 50 km circular buffers around the closest weather station to each population. These buffers encompassed all populations of *E. furcata* used in this study. Within those buffers, we calculated the mean and standard deviation of each climate variable by the seasons described as above. We then shifted the means of the historical frequency distributions by the amounts predicted for the future to obtain a new predicted future mean for each variable (Table 1), but retained the standard deviation estimated from the historic data (Step 2 in Figure S1b).

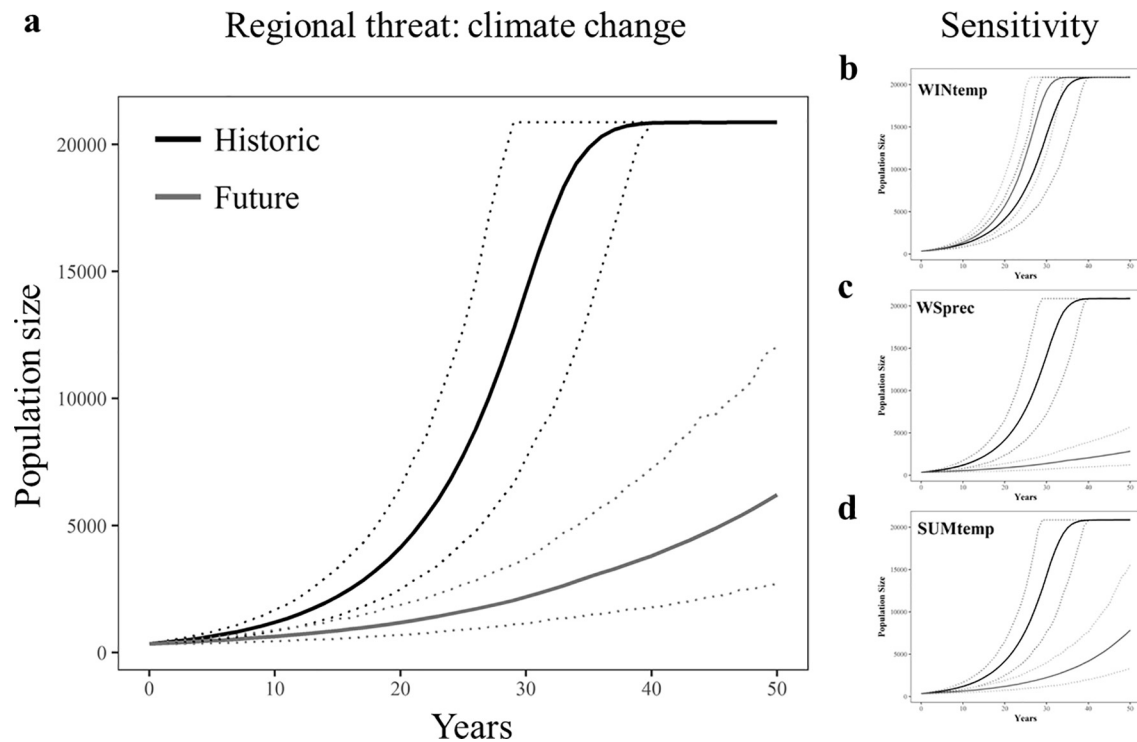
These frequency distributions allowed us to compare population projections based on historic versus future climatic conditions. Thus, again our models assess the relative effect of climate change between historic and future conditions and our results should not be interpreted as absolute estimate of *E. furcata*'s viability. First, we chose a random value from a normal distribution of each climate variable, either future

**Table 1**

Mean and standard deviations of historic climate values calculated from Worldclim data. Future means from predictions described in text.

Variable		Historic Mean	Standard Deviation	Future Mean
Precipitation (mm)				
Total: Dec–May	WSprec	397.7	100.7	437.4
Temperature (°C)				
Average: Dec–Feb	WINtemp	−6.37	0.95	−4.37
Average: Jun–Aug	SUTemp	20.23	0.64	21.23 starting year 36





**Fig. 3.** (A) Model results examining the regional effect of climate change on *Eurybia furcata*. B-D) Results of sensitivity analyses for each climate variable. Solid lines show the change in population size through time averaged across the 1000 replicate simulations. Dotted lines are 95% CI's around the mean.

or historic, characterized by that variable's mean and standard deviation. To calculate a LRR, we fed those variables into a modified regression equation:

$$\text{predicted LRR} = \beta_1 * \text{WSprec} + \beta_2 * \text{WINTemp} + \beta_3 * \text{SUMtemp} \quad (3)$$

using the  $\beta$  values extracted above (Appendix S2: Step 3 in Figure S1b). Then we performed 50-year stochastic projections under each scenario (Appendix S2: Step 4 in Figure S1b) replicated 1000 times (Appendix S2: Step 5 in Figure S1b). The sensitivity of the model projections to each climate variable was assessed by using the historic distribution instead of the future distribution for each variable, one at time, in an otherwise unchanged model. An individual climate variable contributes strongly to the population projection results if we observe substantial changes in projection results with and without the focal climate variable's future distribution included.

## 2.6. Modelling the interactive effect between local and regional threats

We assessed the interactive effect between threats at a local and regional scale by running the climate change projections using the groups of data identified as scenarios for local threats (Fig. 2a; GitHub Data S2). The High Both scenario could not be projected independently due to low sample size of LRR data. Those data were lumped with the Low Deer + Low/High Woody group for this analysis. Thus, we assessed the effect of climate change on *E. furcata* assuming good control of local threats (using the No/Low Both group;  $n = 32$ ) or the presence of local threats (the combined Low Deer + Low/High Woody and High Both groups;  $n = 32$ ). The new correlation coefficients for each scenario were  $\text{WSprec} = 0.0009$ ,  $\text{WINTemp} = -0.0133$  and  $\text{SUMtemp} = -0.0152$ , and  $\text{WSprec} = 0.0001$ ,  $\text{WINTemp} = -0.0628$  and  $\text{SUMtemp} = -0.0169$ , respectively.

## 3. Results

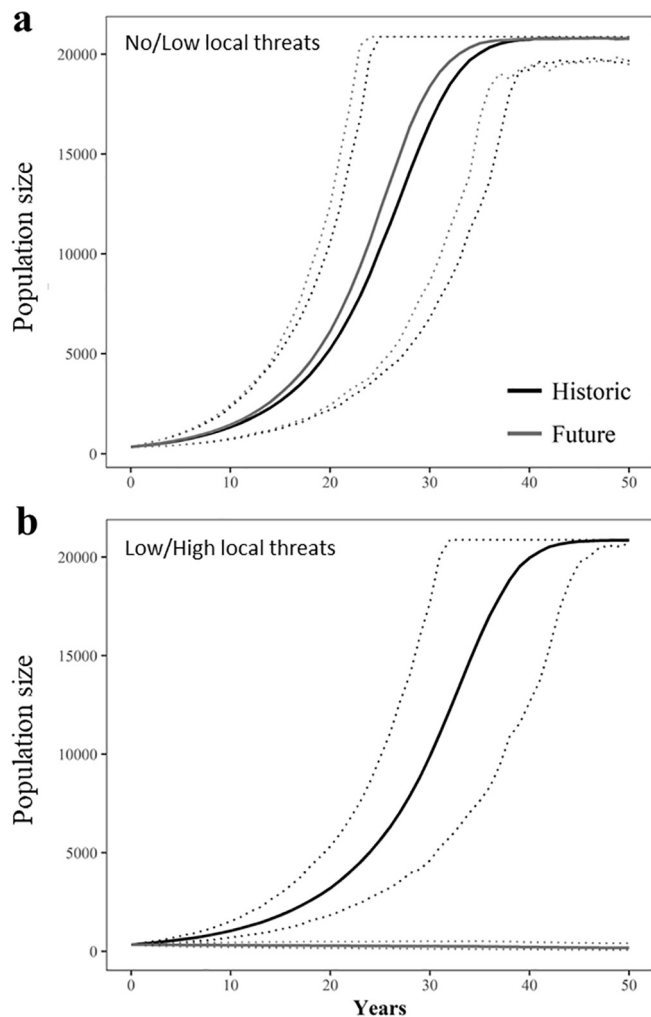
### 3.1. Main effects of local and regional threats

The No/Low Both local threat scenario had a final average population size of 10,511 individuals and a 0.39 probability of extinction (Fig. 2b). The Low Deer + Low/High Woody scenario had a final average population size of 1159 individuals and a 0.46 probability of extinction. Modelling *Eurybia furcata*'s viability with data from sites with lower levels of local threats resulted in an 807% increase in population size and a 7-percentage point reduction in the probability of extinction compared to modelling with data from sites with higher local threats.

Both historic and future scenarios had a 0% chance going extinct. However, the average final population size under historic conditions was 20,864 individuals while the average final population size under future conditions was 6207 individuals (Fig. 3a); a 236% increase in population size under historic versus future conditions. Our model is most sensitive to the increase in winter temperature. Removing the future predictions of winter temperature from the model caused the difference in population size projections for historic and future climate conditions to disappear (Fig. 3b), whereas removal of the future predictions of winter and spring precipitation (Fig. 3c) and summer temperature (Fig. 3d) yielded projection results that were largely similar to the original model.

### 3.2. Interaction between local and regional threats

The effect of climate change on *E. furcata* largely disappears when local threats are low or absent (Fig. 4a). The average final population sizes were 20,794 and 20,764 individuals under historic and future conditions, respectively (a 0.14% increase in population size under historic versus future conditions). Neither scenario had any probability of extinction. However, the effect of climate change is magnified compared to the original climate model when using data that represent



**Fig. 4.** Model results examining the regional effect of climate change on *Eurybia furcata* under (A) No or Low impact of local threats and (B) Low or High impact of local threats. Solid lines show the change in population size through time averaged across the 1000 replicate simulations. Dotted lines are 95% CI's around the mean.

a higher impact of local threats (Fig. 4b). Those final average population sizes were 20,848 and 175 individuals under historic and future conditions, respectively (an 11,813% increase in population size under historic versus future conditions). These scenarios also had no probability of extinction.

## 4. Discussion

### 4.1. Interactions among threats at different spatial scales

We used count based PVAs to reveal strong interactive effects among local and regional threats for a focal plant species. Individually, climate change caused populations to grow more slowly and reach smaller sizes by the end of the projection (Fig. 3b), and such small population sizes are known to threaten the ability of populations to rebound from a catastrophe (Lande, 1993). Climate change also seemed to increase the variability in population size, especially after year 40 for the model (Fig. 3b), which can also put populations more at-risk when they are small (Gabriel and Burger, 1992; Morris and Doak, 2002). But, these effects largely disappeared when we modeled an interaction between climate change and local threats by using data only from sites minimally impacted by local threats (Fig. 4a). This suggests that management actions targeting local threats can improve the viability of *E.*

*furcata* populations both by reducing the risk of extinction due to local those threats and by decreasing this species vulnerability to climate change.

The threat of climate change will act in concert with other anthropogenic factors, such as land use change, overexploitation, and invasive species to influence species' extinction risk (IPCC, 2014). Few studies are available to assess multiple threats, and how these might act to simultaneously and synergistically harm populations. Conservation planning has historically focused on local scale threats but must now adapt to consider the regional threat of climate change (Thomas, 2011). Such planning requires threat analysis from multiple populations and at regional spatial scales. This task may seem daunting, but our results provide an optimistic outlook that count data, which are often readily available as a part of ongoing monitoring frameworks, can be effectively utilized for this purpose.

Our climate change results should be interpreted with caution. First, we only modelled climate change for populations of *E. furcata* in the Western Great Lakes region, which contains the Northern portion of this species range (Fig. 1; NatureServe, 2016). Given the general expectation of poleward migration or expansion due to climate change (Parmesan and Yohe, 2003), it is reasonable to expect a greater measured effect of climate change on populations in the Southern portion of *E. furcata*'s range, which may or may not be influenced by the level of local threats in those populations. If this is the case, focusing on local scale threats in Northern populations would be even more important for decreasing the species wide risk of extinction. Second, it is possible that *E. furcata*'s growth rate responds strongly to climate variables that are not predicted to change drastically, and hence are not included in our model. And again, the effects of those climate variables may or may not be influenced the level of local threats. If this is the case, the persistence of these Northern populations of *E. furcata* could still be threatened by climate change even if local threats are well managed.

### 4.2. Extending the use of count based data

There has been a long debate over the how useful count data are for rare species management (Dennis et al., 1991; Possingham et al., 1993; Beissinger and Westphal, 1998; Sabo et al., 2004). However, recent work supports the validity of this method when used to compare the relative extinction risk among models and for developing management plans (McCarthy et al., 2002; Morris and Doak, 2002; Lotts et al., 2004; Sabo et al., 2004; García et al., 2010). Our work expands on the count based PVA approach to consider multiple, interacting threats acting at multiple spatial scales. By comparing among different count based PVA models we clearly identified that managing local threats directly and indirectly through an interactive effect with climate change increases viability in our system. We suggest that the methodology that we employ here could be readily applied to other rare plant species for which monitoring data are available at multiple populations (Parks, 1993; Bittman, 2001; Havens et al., 2012).

Our count based PVA approach could also be used to incorporate the effects of management in an adaptive management context. Managers typically monitor populations to assess the effect of management actions on the recovery of a population, to detect changes in existing threats through time, and to identify the emergence of new threats. However, to date, few researchers incorporate their adaptive management activities directly into population viability analyses or use population viability analyses more than once to assess the effectiveness of their actions (Bakker and Doak, 2008). Our approach could be easily applied to these goals. For example, in our system our models predict that management of local threats should increase population growth rate, decrease extinction risk, and decrease vulnerability to climate change. If such management were enacted, it would then be easy to reassess our system using our method to determine if those changes occurred to the magnitude expected from our observational data.

### 4.3. Management recommendations for *Eurybia furcata*

We found that local threats decrease the persistence of *Eurybia furcata* in the Western Great Lakes region. Our models indicated that populations are only able to substantially increase when 50% or less of the population is browsed by deer or encroached by woody invasive species (Fig. 2b). However, comparing our two modeled local threat scenarios suggests that the presence of woody invasive species is the larger threat and that low levels of browsing by deer will likely not cause major declines in *E. furcata* populations unless those populations are also highly encroached by woody invasive species. Therefore, we recommend that managers prioritize minimizing woody invasive species encroachment into populations of *E. furcata*. However, despite a sample size too low for projection modelling, the negative impact of high levels of both threats is striking (Fig. 2a). A high local threat of deer browsing was only present at sites that also had high levels of woody invasive encroachment. This could be due to the biology of these factors since deer are known to prefer woodland sites heavily invaded with exotic shrubs (Allan et al., 2010). If sites that currently have high levels of woody invasive encroachment and deer browse are converted to sites with a low abundance of woody invasive encroachment through management, it is unclear if deer would also decrease their use of the sites or if deer would need to be managed separately. This is an important avenue for future research.

### 5. Conclusions

It is well known that multiple threats simultaneously affect plant and animal species (Brook et al., 2008), but the high data requirements of traditional age or stage based population viability analyses mean that these interactive effects, and the optimal management strategies to reduce their synergistic effects, often cannot be assessed. Because count based PVAs require less data this method has the potential to fill these gaps in our knowledge on threats to rare species (McCarthy et al., 2002; Morris and Doak, 2002; Lotts et al., 2004; Sabo et al., 2004; García et al., 2010). To our knowledge, we are the first to use count based PVAs specifically to assess multiple, interacting threats acting on plants at different spatial scales. These models allow us to make recommendations for prioritizing conservation effort among threats to help ensure the best use of conservation resources. This approach can be applied widely to count based monitoring data already in existence. Doing so will result in robust recommendations to land managers on how to prioritize local and regional scale management actions for species of concern, and contribute to a larger framework for understanding how to best combat multiple threats that may act at different scales or have synergistic effects on a species risk of extinction.

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### Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the

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